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Abstract

The study estimates the effect of school starting age on academic performance for Hungarian grade four students using the “Progress in International Reading Literacy Study” (PIRLS) and the “Trends in Mathematics and Science Study” (TIMMS). The study uses the control function approach, exploiting the exogenous variation in school starting age driven by the children’s month of birth and the cut-off date regulation for enrolment. The results indicate a positive age effect on Reading, Mathematics and Science performance.

JEL:

I21, I28, J24

Keywords:
Education, student test scores, enrolment age, identification

A beiskolázási életkor hatása az iskolai eredményekre Magyarországon

Hámori Szilvia

Összefoglaló

A tanulmány a beiskolázási életkor hatását elemzi az iskolai eredményekre Magyarországon a negyedik osztályos tanulók körében a "Progress in International Reading Literacy Study" (PIRLS) adatait és a "Trends in Mathematics and Science Study" (TIMMS) adatait felhasználva. Az eredmények azt mutatják, hogy a későbbi beiskolázási életkornak pozítiv hatása van az iskolai eredményekre, továbbá számos társadalmi-gazdasági tényező, mint például a családi háttér, fontos szerepet játszik az iskolai eredményekben.

Tárgyszavak:

Oktatás, iskolai eredmények, beiskolázási életkor, identifikálás

1. INTRODUCTION

Research in education provides mixed theories and evidence on the optimal age at which children should start school.[1] According to the proponents of late school starting age, starting school at an older age ensures that children have sufficient time to acquire the human capital necessary for educational success. In addition to the intellectual competencies of concentration and the ability to follow instructions, which children gain as they age, emotional aspects, such as being able to be apart from the parents, and social ones, such as being able to share with other children, play a significant role in success in school. Opponents of delayed school entry argue that (a) the advantage of late school entry may be modest and transitory and (b) the emphasis should be placed on "making schools ready for children rather than making children ready for school"[2], in the sense that teaching and learning opportunities should be tailored to the intellectual, emotional and social skills of children. From an economic perspective, the potential academic gains of starting school later need to be weighted against the economic losses of entering the labour market later, given that eventual educational attainment and retirement age are unaffected. These economic losses entail the obvious monetary and productivity losses of entering the labour market a year later as well the early additional childcare costs imposed on the parents.

There is an extensive recent empirical economic literature concentrating on the relationship between academic outcomes and school starting age.[3] The difficulty in estimating the effect of school starting age on academic performance arises from the fact that there is a choice regarding enrolment decision despite the cut-off date regulation. Given a certain degree of discretion regarding enrolment decisions, based on teacher's recommendation, boards of specialists giving school readiness tests assessing emotional and intellectual readiness, and most importantly parental choice, the group of students with early/delayed entry does not represent a non-random sample. That is, whereas early entrants come from (a) the pool of higher ability children, as well as (b) from ambitious parents who want an early start (regardless of ability), the late starters come from (c) the pool of lower ability children and (d) potentially from wealthier families (for whom the burden of additional childcare costs may be irrelevant). Given this non-random selection, late starters may be, on average, lower ability children and thus regressing academic performance on actual school starting age by

[1] For an extensive review of the theories and findings in educationalist literature see Stipek (2002).

[2] Stipek (2002), p. 14.

[3] For evidence on the effect of school starting age on academic performance see, among others, Leuven et al. (2004) for evidence on the Netherlands, Strøm (2004) on Norway, Frederikkson and Öckert (2005) on Sweden, Puhani and Weber (2006) and Fertig and Kluve (2005) on Germany and Bedard and Dhuey (2005) on a number of OECD countries.

ordinary least squares (OLS) may generate a downward biased estimate of the age effect on academic performance.

In order to overcome the problem of non-random selection in countries where the cut-off date regulation is not exogenous, the empirical literature has concentrated on instrumental variable estimation (IV), that is, finding a valid instrument for actual school starting age which is (1) correlated with actual school starting age and (2) uncorrelated with the unobserved determinants of academic performance i.e. ability. Numerous studies[4] have hence exploited the exogenous variation in school starting age driven by (1) the cut-off date for enrolment and (2) the children's month of birth, which generates the "expected school starting age". Accordingly, the empirical strategy is to use the "expected school starting age" as an instrument for "actual school starting age". It is important to note that the IV approach identifies the local average treatment effect (LATE), that is, the average causal effect of school starting age on academic performance for the group of "compliers", who are defined as those individuals whose school entry age is affected by the instrument used (introduced by Imbens and Angrist (1994)). At this point is important to clarify that the group of "LATE-compliers" is not equivalent to the group of students who enroll on time. The latter group, using the definitions of Angrist et al. (1996), is composed of the "LATE-compilers" as well as "always-takers" who are unaffected by the particular instrumental variable, that is, those who always enroll on time regardless of the value of the instrument to which they might be exposed. Subsequently, throughout the paper the group of "LATE-compliers" and "those enrolling on time/complying with the cut-off date regulation" will not refer to the same student population.

The studies using the IV estimation strategy described above analyse the effect of school starting age on academic performance in various countries, using different age groups (for example, second, fourth and eighth graders), different subsamples (such as minority students or students with lower educated parents in the Netherlands) and different outcomes of interest, ranging from which track a student chooses (for example, academic versus vocational in Germany) to test scores in different subjects. A number of studies, namely Leuven et al. (2004) on the Netherlands (for some subsamples), Strøm (2004) on Norway, Frederikkson and Öckert (2005) on Sweden, Puhani and Weber (2006) on Germany and Bedard and Dhuey (2005) on a number of OECD countries find evidence that (1) the OLS estimate of the association between age and schooling outcomes is negative, attributing this to the non-random selection of earls/late starters and (2) the IV regression, described above, yields a

[4] For empirical evidence using IV estimation in order to estimate the causal effect of school starting age on academic performance see, among others, Leuven et al. (2004) for evidence on the Netherlands, Strøm (2004) on Norway, Frederikkson and Öckert (2005) on Sweden, Puhani and Weber (2006) and Fertig and Kluve (2005) on Germany and Bedard and Dhuey (2005) on a number of OECD countries.

yields a positive LATE estimate, which differs in magnitude across countries. Exceptions are the study by Fertig and Kluve (2005) who provide evidence that there is no effect of age at school entry on educational outcomes in Germany.

The aim of this paper is to estimate the effect of school starting age on academic performance in Hungary – a country for which, despite the vast recent international evidence, such analysis has not been carried out to this date. It is important to extend the international evidence because, as outlined above, the effect of age on schooling performance is not clear from the outset and the cross-country differences may be caused by, among other factor, the different educational structures, which may equalise opportunities among students to different degrees.

In Hungary, the school starting age regulation requires children who turn six years old by the 31st of May to start school on the 1st of September in the corresponding year.[5] Children born after that date need to wait an additional year in order to enroll. In Hungary, as in some other countries such as Germany or the US, the school cut-off date regulation is not exogenous, given that there is teacher, specialists and parental discretion regarding the school starting age. For example, for the samples under analysis, children who are born in the summer months may start school at the age of six instead of waiting another year, and those who are born just before the cut-off date may wait another year to enroll instead of starting at the age of six. Given the degree of discretion regarding enrolment, i.e. non-random selection of early/delayed school starters in Hungary, an OLS regression of academic achievement on school starting age may yield a downward biased estimate of the (mean) age effect, as described above.

Therefore, in addition to the standard OLS regressions, the paper uses an extension to the IV strategy of the existing literature, using "expected school starting age" as an instrument for "actual school starting age", namely, the control function approach, proposed by Garen (1984) and Heckman and Robb (1985). The advantage of the control function approach over the IV estimation strategy is that in addition to the bias due to non-random selection of early/late entrants outlined above, it also accounts for the individual heterogeneity in the age effect. Whereas the IV estimand captures the average causal effect for the group of "compliers", as defined above, which may not be representative of the entire population, the control function approach estimates the average treatment effect (ATE), which reflects the age effect on academic performance for a random individual.

[5] Note that the cut-off date for enrollment prior to 1986 was August 31st rather than May 31st. All the samples under analysis have started school according the May cut-off date regulation, hence the change in regulation does not cause a problem for the purposes of this paper. See Vágó (2005) for further detail on the cut-off date regulation in Hungary.

The data for the analysis is drawn from the “Progress in International Reading and Literacy Study (PIRLS)” and the “Trends in Mathematics and Science Study (TIMSS)”, which were collected in 2001 and 2003 respectively at the grade four level. Therefore, the paper analyses the effect of age on different areas of schooling performance, namely Reading, Mathematics and Science. Although the key parameter of interest of the paper is the effect of age on test scores, the effect of numerous other determinants of academic performance, such as gender, family size, parental education, home possessions (depending on the availability of data) are analysed.

The OLS results suggest that the relationship between the actual school starting age and Reading, Mathematics and Science test scores at the fourth grade level is negative, for the samples as a whole as well as for subsamples split by gender and parental education. This negative association is driven by the fact that early starters are, on average, selected from the pool of well-performing students, and late starters are selected from the pool of underachievers and hence cannot be interpreted as the causal effect of age on performance. The estimates from the control function approach switch the sign of the effect of age on schooling outcomes, indicating a positive effect of school starting age on academic performance. For example, in the full sample the point estimate for the PIRLS is around 6 points, which corresponds to 10 percent of the standard deviation in the Reading test scores. The corresponding figures are approximately 15 points and 18 points for Mathematics and Science, which correspond to 21 percent and 24 percent of the standard deviation of the Mathematics and Science test scores respectively. The effect of the other explanatory variables, namely gender, parental education, family size, and proxies for economic wealth play a significant role in academic performance, their effects are as expected and are robust across subjects and subsamples of students. For instance, the gender achievement gap is in favour of girls for Reading and in favour of boys for Mathematics and Science, which amounts to around 22, 10 and 12 percent of the standard deviation of the Reading, Mathematics and Science test scores respectively. Moreover, the incremental (mean) Reading score for children whose parents (at least one parent) hold(s) a high school degree relative to those whose parents at most finished primary school is around 89 percent of the standard deviation of the Reading scores and those students who have more than two siblings score around 46 percent of the standard deviation of the Reading tests lower than single children.

The remainder of the paper is organised as follows: Section 2 proceeds with a presentation of the data and some descriptive statistics, Section 3 describes the empirical strategy, focusing on the problems with OLS regression when estimating age effects on educational attainment, the instrument used and the control function approach, Section 4 describes the empirical results obtained and finally Section 5 concludes. Tables for the descriptive statistics and the estimation results are presented in appendices 1 – 4.

2. DATA AND DESCRIPTIVE EVIDENCE

2.1. PROGRESS IN INTERNATIONAL READING LITERACY STUDY (PIRLS), 2001

The data for reading literacy is drawn from "Progress in International Reading Literacy Study" (PIRLS), which is available for 2001 for 35 countries. The sample of students assessed consists of fourth graders who were tested at the end of the academic year. Fourth graders were chosen because grade four represents an important stage in a child's development as a reader as by the end of fourth grade children are expected to have learned to read efficiently and so are reading in order to learn. The children are tested on four areas (via multiple choice and constructed response), namely (1) retrieving explicitly stated information, (2) making straightforward inferences, (3) interpreting and integrating ideas and information and (4) examining and evaluating content and language, based on the booklet they are given which consists of two blocks of either literary text or informational text.[6]

The paper merges data from the Student Questionnaire and the Home Survey, which include the Reading test scores and basic student background information and demographic and socio-economic indicators respectively. The outcome variable of interest is the Reading score, which is standardized so that the mean is equal to 500 and the standard deviation equals 100 when all countries are weighted equally. The control variables included in the regression are the standard variables that are likely to be significant determinants of student achievement, namely gender, parental education, family size and some indicator for household income, Accordingly, five categories for parental education[7] and for the number of siblings[8] respectively are generated, and dummy variables indicating gender and whether the family owns a car, as an indicator of family income, are included in the regression equation[9]. The number of observations in the sample is 4,508.

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[6] For an extensive description of the PIRLS dataset, testing procedure, scoring guide see Eugenio and Kennedy (Eds.) (2003).

[7] The categories for parental education (which are more aggregated than those reported in the dataset due to sample size considerations) have been generated using the seven highest schooling degrees completed reported for each parent separately in the dataset, namely, "did not go to school", "ISCED level 2" (eight years of primary school), "ISCED level 3a,b" (high school degree), "ISCED level 3c" (lower level vocational degree), "ISCED level 4a" (higher level vocational degree), "ISCED level 5a" (college degree) and "ISCED level 5b" (university degree). These seven schooling degrees are coded into five possible "parental educational groups" (see Table 1 in Appendix 1 for detail), whereby (a) at least one parent has the corresponding degree and (b) the groups represent a ranking in terms of the level of education. Those observations with missing educational information for both parents are in the Missing category.

[8] There is a variable in the dataset indicating the number of children living at home, ranging from one to more than ten (i.e. eleven categories), which have been aggregated into five groups (see Table 1 in Appendix 1 for detail).

[9] Among others, Behrman and Taubman (1986) provides extensive theoretical background and econometric evidence on the effects of birth order, family size, parental education and parental family earnings on the years of schooling.

Table 1 in Appendix 1 provides summary statistics of the variables used in the analysis. Note that the mean Reading score in the Hungarian sample is around 45 points above the international mean of 500 points. Not surprisingly, mean Reading scores differ by gender and parental background, namely girls and students with academic parents respectively attain a higher score in the sample. In terms of the control variables included in the regression analysis it is interesting to note that approximately 43 percent of the sample have parents with vocational degrees, and around half of the sample come from families with two children. Note also that mean actual school starting age, measured in yearly units (varying by month of birth) is slightly higher than mean expected school starting age (i.e. six years and eleven months versus six years and ten months), which reflects (a) that the majority of the students do enroll on time and (b) for those who do not enroll on time a tendency (on average) towards later enrolment.

2.2. TRENDS IN MATHEMATICS AND SCIENCE STUDY (TIMSS), 2003

The data for Mathematics and Science scores is drawn from the most recent, 2003, "Trends in Mathematics and Science Study" (TIMSS), which has been conducted in 48 countries. Like in PIRLS, the sample of students assessed consists of fourth graders who were tested at the end of the academic year. Similarly to PIRLS, the fourth grade students were tested in various areas, namely (1) knowing facts and procedures, (2) using concepts, (3) solving routine problems and (4) reasoning for Mathematics and (1) factual knowledge, (2) conceptual understanding and (3) reasoning and analysis for Science respectively, (whereby the broad field of Science is composed of three content domains, namely Life Science, Physical Science and Earth Science).[10]

The outcome variables of interest are the Mathematics score and Science score respectively. As for the PIRLS, the TIMMS mean score for Mathematics and Science for the participating countries is set at 500 and the standard deviation at 100. The control variables include five categories for the number of persons living at home[11], dummy variables indicating gender and whether the family owns a VCR, and four categorical variables for doing well in Mathematics and Science respectively. Unfortunately, a drawback of the TIMSS at the fourth grade level is that information on parental education background is not available. The number of observations in the sample is 3,222.

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[10] For an extensive discussion of the TIMSS dataset, the content and cognitive domains tested for Mathematics and Science respectively, the test design and scoring guide see Martin (Eds.) (2005)

[11] There is a variable in the dataset indicating the number of persons living at home, ranging from two to eight or more (i.e. seven categories), which have been merged into five groups (see Table 2 in Appendix 1) in an identical way as categories for number of siblings in the PIRLS dataset.

Table 2 in Appendix 1 provides summary statistics of the variables used in the analysis. Note that the mean Mathematics and the mean Science scores in the Hungarian sample are approximately 30 and 28 points above the international mean of 500 points respectively. Boys attain higher scores in both Mathematics and Science than girls, in opposition to Reading. Approximately 42 percent of the sample comes from families with four persons living at home. As in the PIRLS 2001 data, in the TIMMS data the mean actual school starting age measured in years (varying by month) is slightly higher than mean expected school starting age (i.e. seven years versus six years and ten months), which again reflects (a) that the majority of the students do enroll on time and (b) for those who do not enroll on time a tendency (on average) towards later enrolment.

3. ESTIMATION STRATEGY

3.1. ORDINARY LEAST SQUARES

The paper first estimates the effect of school starting age on scholastic achievement using a simple specification:

$$Y_i = \beta_1 + \beta_2 A_i^s + X_i' \beta_3 + \varepsilon_i, \qquad i = 1, \ldots, n \quad (1)$$

where Y_i is test score for individual i, A_i^s is actual school starting age, X_i represents a vector of student and family background variables that may influence student performance, such as gender and number of siblings, and ε_i is a random disturbance term which contains the unobserved determinants of student performance such as ability. The key parameter of interest is β_2, the age effect.

The problem with estimating equation (1) by ordinary least squares (OLS) is that the given that the cut-off date regulation is not exogenous, i.e. there is teacher and parental discretion, the early/late school entrants represent a non-random sample. That is, it is possible that (a) ambitious parents may prefer an early enrolment (b) wealthier parents may prefer a later start irrespective of the additional childcare costs and (c) children with lower and higher abilities may start school a year later and earlier than proposed by the cut-off date regulation respectively i.e. $Cov\left(A_i^S, \varepsilon_i\right) \neq 0$. If the non-random pattern of enrollment is such that, on average, less able children enter school a year later, the OLS estimate for the effect of school starting age on test score β_2 may be downward biased.

3.2. INSTRUMENTAL VARIABLES ESTIMATION

In order to overcome the problem of non-random selection of early/late school entrants, the recent empirical literature has proposed instrumental variable estimation (IV), using an instrument for actual school starting age A_i^S which is (1) correlated with actual school starting age and (2) uncorrelated with the unobserved determinants of academic performance (most importantly ability. The IV approach in the existing literature exploits the exogenous variation in school starting age driven by the children's month of birth and the cut-off date regulation for enrolment. Accordingly, expected school starting age A_i^E, defined as the age when the child is supposed to start school according to the cut-off date regulation and his/her month of birth, is used as the instrument for actual school starting age A_i^S.[12] As outlined in the Introduction, the IV approach described above estimates the average causal effect of age on academic performance for the group of "compliers", who are composed of the individuals who alter their school entry age in response to the instrument. The average effect for the group of "compliers" is called the local average treatment effect (LATE), discussed by Imbens and Angrist (1994), Angrist and Imbens (1995) and Angrist et al. (1996), which may not be representative for the entire population. Therefore, the papers using the IV strategy characterize how school starting age influences academic outcomes for the group of "LATE-compliers" and hence the estimates must be interpreted accordingly.

Formally, in the IV approach, the first stage regression involves a regression of A_i^S for individual i on the instrument A_i^E and the vector of control variables X_i, such as student and family background variables, to obtain the fitted values $\hat{A}_i^S$:

$$A_i^S = \alpha_1 + \alpha_2 A_i^E + X_i'\alpha_3 + \mu_i, \qquad i = 1,\dots,n \qquad (2)$$

where μ_i is a random disturbance term which contains the unobserved determinants of children's actual school entry age such as intellectual, mental and social maturity.

The second stage involves a regression of test score Y_i for individual i on $\hat{A}_i^S$ and X_i:

$$Y_i = \beta_1 + \beta_2 \hat{A}_i^s + X_i'\beta_3 + \varepsilon_i, \qquad i = 1,\dots,n \quad (3)$$

[12] For examples see, among others, Leuven et al. (2004) for evidence on the Netherlands, Strøm (2004) on Norway, Frederikkson and Öckert (2005) on Sweden, Puhani and Weber (2006) and Fertig and Kluve (2005) on Germany and Bedard and Dhuey (2005) on a number of OECD countries.

where ε_i is a random disturbance term which contains the unobserved determinants of student performance such as ability. The IV estimation approach yields the LATE estimate of age effect β_2 .

3.3. CONTROL FUNCTION APPROACH

Unlike the previous studies which used the IV estimation approach, this paper uses the control function approach, outlined by Garen (1984) and Heckman and Robb (1985). The control function approach is an extension to the IV approach. The advantage of the control function approach over the IV estimation strategy is that in addition to the bias due to the correlation between the unobserved determinants and actual school starting age (for reasons outlined in detail in Section 3.1), in this context called the "absolute advantage bias", it also accounts for the individual heterogeneity in the age effect.

More precisely, if individuals differ in their academic ability at different ages, they have a comparative advantage at certain ages. That is, the age effect is not constant for all ages for an individual. If the parents of the children/teachers know the comparative advantage of the particular child and act accordingly, they will enroll the child at the age which yields the highest return (i.e. age effect). In this case, the age effect and the actual age at school entry will be correlated, causing a bias in the estimated age effect. This is the additional source of bias, the so-called "comparative advantage bias", which the control function approach controls for.

Formally, the model consists of two equations. The first equation (as in the IV estimation approach described above), keeping to the notation in the previous subsection, involves the relationship between actual school entry age A_i^S for individual i and the instrument, A_i^E and a vector of other control variables X_i:

$$A_i^S = \alpha_1 + \alpha_2 A_i^E + X_i'\alpha_3 + \varepsilon_{Si} \qquad i = 1,\ldots,n \quad (4)$$

where ε_{Si} is a random disturbance term which contains the unobserved determinants of children's actual school entry age such as intellectual, mental and social maturity.

For simplicity of notation, Equation (4) can be rewritten as:

$$A_i^s = Z_i'\alpha + \varepsilon_{Si} \qquad i = 1,\ldots,n \quad (5)$$

where Z_i represents the vector of explanatory variables from Equation (4).

The second equation of the model, the "test equation", involves the relationship between test score Y_i for individual i and A_i^S and a vector of exogenous regressors X_i which affect test score such as student and family background variables:

$$Y_i = \gamma_1 + \gamma_{2i} A_i^S + X_i^{'} \gamma_3 + \varepsilon_i \qquad i = 1, \ldots, n \quad (6)$$

where ε_i is a random disturbance term which contains the unobserved determinants of student performance such as innate ability. Taking into account the two sources of unobserved heterogeneity outlined above, the "test equation"(6) can be rewritten as follows:

$$Y_i = \gamma_1 + \overline{\gamma_2} A_i^S + X_i^{'} \gamma_3 + \varepsilon_i + \left(\gamma_{2i} - \overline{\gamma_2}\right) A_i^S \qquad i = 1, \ldots, n \quad (7)$$

where $\overline{\gamma}_2$ is the average age effect and $\varepsilon_i + \left(\gamma_{2i} - \overline{\gamma_2}\right) A_i^S$ is a composite disturbance term, which represents the two sources of unobserved heterogeneity.

For simplicity of notation denoting the term $\left(\gamma_{2i} - \overline{\gamma_2}\right) \equiv \eta_i$ and the exogenous variables Z_i and X_i in equations (5) and (7) respectively by r_i the conditional expectation of the composite error term $\varepsilon_i + \left(\gamma_{2i} - \overline{\gamma_2}\right) A_i^S$ is:

$$\begin{aligned} E\left(\varepsilon_i + \eta_i A_i^S \mid A_i^S, r_i\right) &= E\left(\varepsilon_i + \eta_i A_i^S \mid A_i^S = Z_i^{'}\alpha + \varepsilon_{Si}, r_i\right) \\ &= E\left(\varepsilon_i \mid \varepsilon_{Si} = A_i^S - Z_i^{'}\alpha, r_i\right) + E\left(\eta_i \mid \varepsilon_{Si} = A_i^S - Z_i^{'}\alpha, r_i\right) \cdot A_i^S \end{aligned} \qquad i = 1, \ldots, n \quad (8)$$

$$E\left(\varepsilon_i \mid \varepsilon_{Si} = A_i^S - Z_i^{'}\alpha, r_i\right) = \frac{Cov\left(\varepsilon_{i,} \varepsilon_{Si}\right)}{Var\left(\varepsilon_{Si}\right)} \cdot \varepsilon_{Si} \qquad i = 1, \ldots, n \quad (9)$$

$$E\left(\eta_i \mid \varepsilon_{Si} = A_i^S - Z_i^{'}\alpha, r_i\right) = \frac{Cov\left(\eta_i, \varepsilon_{Si}\right)}{Var\left(\varepsilon_{Si}\right)} \cdot \varepsilon_{Si} \qquad i = 1, \ldots, n \quad (10)$$

Therefore, the conditional expectation of the "test equation" (7) is:

$$E\left(Y_i \mid A_i^S, X_i, Z_i\right) = \gamma_1 + \overline{\gamma_2} A_i^S + X_i^{'}\gamma_3 + \frac{Cov\left(\varepsilon_i, \varepsilon_{Si}\right)}{Var\left(\varepsilon_{Si}\right)} \cdot \varepsilon_{Si} + \frac{Cov\left(\eta_i, \varepsilon_{Si}\right)}{Var\left(\varepsilon_{Si}\right)} \cdot \varepsilon_{Si} \cdot A_i^S \quad i = 1, \ldots, n \quad (11)$$

As the last two terms in (12) are nonzero, OLS estimation of the "test equation" will yield inconsistent estimates of the effect of age on test score.

Obtaining a consistent estimate of ε_{Si}, $\hat{\varepsilon}_{Si}$, and including $\hat{\varepsilon}_{Si}$ and the interaction of $\hat{\varepsilon}_{Si}$ and A_i^S as regressors in the "test equation" corrects for the bias caused by the unobserved factors. Consistent estimate of the error term, $\hat{\varepsilon}_{Si}$, can be obtained from the OLS estimation of equation (5).

Accordingly, the control function regression consists of a two stage procedure. The first stage involves OLS estimation of Equation (5):

$$A_i^S = Z_i^{'}\alpha + \varepsilon_{Si} \qquad i = 1, \ldots, n \quad (12)$$

to obtain the fitted values $\hat{\varepsilon}_{Si} = A_i^S - Z_i^{'}\hat{\alpha}$.

Before coming to the second equation, the choice and the generation of the instrument merits comment. This paper also builds on the use of "expected school starting age" as an exogenous determinant of "actual school starting age", as discussed above, given the institutional features of the Hungarian education system.

In Hungary, the school starting age regulation requires children who turn six years old (72 months old) by the 31st of May to start school on the 1st of September in the corresponding year. Children born after that date need to wait an additional in order to enroll. Therefore, the "expected school starting age" A_i^E, in yearly units (varying by the month of birth), is generated using to the cut-off regulation c and birth month b_i for individual i is as follows:

$$A_i^E = \begin{cases} \dfrac{72 + 9 - b_i}{12} & if \ 1 \le b_i \le c \\ \dfrac{84 + 9 - b_i}{12} & if \ c < b_i \le 12 \end{cases} \qquad i = 1, \ldots, n \quad (13)$$

Given that the cut-off date is May $c=5$, A_i^E is between 6.33 years for the youngest children born in May, which corresponds to 6 years and 4 months, and 7.25 years for the oldest children born in June, which corresponds to 7 years and 3 months. More precisely, for children born between September, who start school at age seven, and those born in May, there is a month-for-month decrease A_i^E. Children born after the cut-off date, May, are required to wait until the following September to enroll in school and thus A_i^E jumps up by 11 months between May and June children and again falls by month between June and August.

Figures 1 and 2 in Appendix 1 provide graphical illustrations of A_i^S and A_i^E for the PIRLS and the TIMSS datasets respectively. Before proceeding with a description of the Figures it important to recall the distinction discussed in detail in the Introduction between the group of students who comply with the cut-off-date regulation i.e. enroll on time and the group of "LATE-compliers", who alter their school entry age in response to the particular instrument. The discussion of the Figures in what is to follow refers to the former group. First of all, note that the figures reaffirm the pattern which emerges from the summary statistics from Tables 1 and 2 in Appendix 1, namely (a) that the majority of students enrolls on time and (b) for those not enrolling on time, there is a tendency (on average) towards late enrolment. The particular pattern of compliance to the cut-off date regulation merits comment: (a) compliance in both years under analysis is weaker in the first six months of the year than in the latter six months and (b) June and July (the months just after the cut-off date) are the only months characterized, on average, by early entry. Visual inspection suggests that the broad pattern of the (average) tendency towards late entry with the exception of the months just after the cut-off date characterize, among other countries, Germany.[13]

The second stage regression consists of a regression of test score Y_i for individual i on A_i^S, X_i and the two additional regressors: the estimated residual from the first stage regression $\hat{\varepsilon}_{Si}$ and the interaction of A_i^S and $\hat{\varepsilon}_{Si}$:

$$Y_i = \gamma_1 + \overline{\gamma_2} A_i^s + X_i'\gamma_3 + \gamma_4 \hat{\varepsilon}_{Si} + \gamma_5 A_i^s \hat{\varepsilon}_{Si} + \varepsilon_i \qquad i = 1,\ldots,n \quad (14)$$

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[13] For a comparison to (a) Germany as a whole using the 2003 PIRLS data and "Pupil-Level Data of the Statistics of General Schools for the State of *Hessen* 2004/2005" see Figure 3 p. 39 in Puhani and Weber (2006) and to (b) the former West and to (c) the former East Germany using the "Young Adult Longitudinal Survey 1991 – 1995/1996" see Figures 1 and 2 pp. 12 – 13 respectively in Fertig and Kluve (2005).

where ε_i is the random disturbance term. The inclusion of $\hat{\varepsilon}_{Si}$ and the interaction of A_i^S and $\hat{\varepsilon}_{Si}$ as additional regressors purges the relationship between test score and actual school starting age of the "absolute advantage bias" and of the "comparative advantage bias" respectively. The control function approach yields consistent estimates for the average effect of age on test score for a random individual $\overline{\gamma}_2$ which is equivalent of the average treatment effect (ATE).

4. ESTIMATION RESULTS

4.1. PIRLS – OLS RESULTS

Table 3 in Appendix 2 reports the parameter estimates for the OLS regressions for the entire sample and the subsamples split by gender and parental educational background respectively for the PIRLS.

The OLS estimation results indicate a negative association between Reading test scores and actual school starting age for the full sample and for both of the subsamples. This negative relationship is driven by the fact that, on average, early and delayed school starters are selected from the pool of high and lower ability children respectively.

Although the parameter of interest is the age effect on Reading performance, the effect of the other control variables is worth commenting on. First, boys, on average, attain a lower score in Reading than girls at the fourth grade level, by approximately 14 points, which corresponds to around 22 percent of the standard deviations in the PIRLS scores for the full sample. Moreover, parental education plays a significant role in educational success, that is, there is a "score premium" associated with the additional degree levels of the parents. For instance, the incremental (mean) Reading score for children whose parents (at least one parent) hold(s) a high school degree relative to those whose parents at most finished primary school is around 54 points for the entire sample, which corresponds to 89 percent of the standard deviation. Those children whose parents do not own a car score lower on the Reading test, by around 15 points for the full sample, which corresponds to 25 percent of the standard deviation. Finally, as expected, the number of siblings is a significant determinant of Reading scores. For example, for the full sample of students those who have more than two siblings score around 28 lower relative to single children, which corresponds to 46 percent of the standard deviation. Note that the effect of these latter two variables remains stable in sign and magnitude across the subsamples.

4.2. PIRLS – CONTROL FUNCTION APPROACH RESULTS

Table 4 in Appendix 2 reports the parameter estimates for the control function approach for the full sample and the subsamples split by gender and parental educational background respectively for the PIRLS. The coefficient estimates for the other covariates not reported, as they are similar in sign and magnitude to the OLS coefficient estimates.

First, note that the first stage coefficient estimates are significant for the full sample and all the subsamples under analysis.[14] The control function approach, which estimates ATE, reverses the relationship between the school starting age and academic performance, that is, the estimate is positive for the full sample and for all of the subsamples considered. For the full sample the point estimate for the age effect is around 6 points, which corresponds to 10 percent of the standard deviation in the Reading scores for the full sample. The estimated age effect is the highest for boys, around 13 points, which corresponds 21 percent of the standard deviation in the Reading test scores for the sample of boys. Hence, the control function approach indicates that (a) the simple OLS regression of Reading scores on actual school starting age is downward biased and (b) when controlling for "absolute advantage bias" and for the bias arising from the individual heterogeneity of the age effect (discussed above) the estimated age effect is positive.

4.3. TIMMS, MATHEMATICS – OLS RESULTS

Table 5 in Appendix 3 reports the parameter estimates for the OLS regressions for the entire sample and for the separate samples of boys and girls respectively for the TIMMS, where the outcome of interest is the Mathematics score for the fourth graders.

The OLS estimation results indicate a negative relationship between Mathematics test scores and actual school starting age for the full sample and boys and girls separately. Again this negative relationship is driven by the fact that, on average, early and delayed school starters are selected from the pool of high and lower ability children respectively.

In terms of the other explanatory variables it is worth noting that, the (average) gender achievement gap is in favor of boys, unlike for Reading, which amounts to approximately 7 points, corresponding to 10 percent of the standard deviation in the TIMMS Mathematics scores for the full sample of fourth graders. Turning to the variable which serves as a proxy for household income, those children whose parents do not own a VCR, score lower on the Mathematics test, by around 23 points for the full sample, which corresponds to 31 percent of the standard deviation. Moreover, family size is a significant determinant of Mathematics

[14] The first stage F-statistics (testing the hypothesis that the instrument, expected school starting age, does not enter the first stage regression) never take on a value less than 10 for any of the samples considered in any of the datasets, which indicates that there is no problem of weak instruments (see Staiger and Stock (1997)).

performance. For example, for the full sample of students those students from households with more than five people score around 31 points lower relative to single children (or two children with single parents), which corresponds to 42 percent of the standard deviation, which reaffirms the notion that children in larger families possibly receive less educational resources/attention than single children. Finally, note that the effect of these latter two variables remains similar in sign and magnitude across the subsamples of girls and boys.

4.4. TIMMS, MATHEMATICS – CONTROL FUNCTION APPROACH RESULTS

Table 6 in Appendix 3 reports the parameter estimates for the control function approach for the full sample and for girls and boys separately for the TIMMS, where the outcome of interest is the Mathematics score. The coefficient estimates for the other covariates not reported, they are similar in sign and magnitude to the OLS coefficient estimates.

The coefficient estimates confirm the same picture for Mathematics performance as for Reading performance: (1) the first stage coefficient estimates are significant for the full sample and for the subsamples of boys and girls separately, (2) the ATE estimates of age effect are above the OLS estimates. For the full sample the ATE estimate of the age effect is around 15 points, which corresponds to 21 percent of the standard deviation in the Mathematics scores for the full sample.

4.5. TIMMS, SCIENCE – OLS RESULTS

Table 7 in Appendix 4 reports the parameter estimates for the OLS regressions for the entire sample and for boys and girls respectively for the TIMMS, where the outcome of interest is the Science score for the fourth graders.

As for the Reading and Mathematics scores, the OLS estimation results indicate a negative relationship between Science test scores and actual school starting age for the full sample and boys and girls separately, which again indicates that, on average, those children who start school later/earlier come from the pool of lower/higher ability students . The (average) gender achievement gap in favor of boys is similar to that in Mathematics: approximately 9 points, which corresponds to 12 percent of the standard deviation in the TIMMS Science scores for the full sample of fourth graders. Not surprisingly, the effects of the other covariates on Science performance are similar in sign and magnitude as for the Mathematics performance. Namely, those children whose parents do not own a VCR are found to have a lower score on the Mathematics test by around 22 points for the full sample, which corresponds to 29 percent of the standard deviation. For the full sample of students, those students from households with more than five people score around 29 points lower relative to single children (or two children with single parents), which corresponds to 39 percent of the standard deviation. Finally, note that the effect of these latter two variables is robust across the subsamples of girls and boys.

4.6. TIMMS, SCIENCE – CONTROL FUNCTION APPROACH RESULTS

Table 8 in Appendix 4 reports the parameter estimates for the control function approach for the full sample and for girls and boys separately for the TIMMS, where the outcome of interest is the Science score. The coefficient estimates for the other covariates not reported, as they are similar in sign and magnitude to the OLS coefficient estimates.

The coefficient estimates confirm the same picture for Science performance as for Mathematics and Reading performance: (1) the first stage coefficient estimates are significant for the full sample and for the subsamples of boys and girls separately, (2) the estimated age effect of the control function approach exceed the corresponding OLS estimates. For the full sample the point estimate of the age effect is around 18 points, which corresponds to 24 percent of the standard deviation in the Science scores for the full sample.

5. CONCLUSION

This study examined the relationship between school starting age and academic performance for grade four students in Reading, Mathematics and Science in Hungary. The challenge in estimating the effect of school starting age on academic performance arises due to the fact that there is choice regarding enrolment decisions and so it is a non-random sample of students who start school earlier/later than dictated by the cut-off date regulation for enrollment. Given this non-random selection, on average, those who delay school entry come from the pool of lower academic ability children and thus regressing academic performance on actual school starting age by OLS may generate a downward biased estimate of the age effect. In order to overcome the problem of non-random selection in countries where the cut-off date regulation is not exogenous, the empirical literature has concentrated on instrumental variable estimation, exploiting the exogenous variation in school starting age driven by (1) the cut-off date for enrolment and (2) the children's month of birth, which generates the "expected school starting age" as an instrument for "actual school starting age". It is important to note that the IV approach identifies the local average treatment effect (LATE), that is, the average causal effect of school starting age on academic performance for the group of "compliers", who are defined as those individuals whose school entry age is affected by the instrument used (introduced by Imbens and Angrist (1994)).

Similarly to the existing literature investigating the effect of school age on schooling outcomes, this paper uses "expected school starting age", defined as the age when the child is supposed to start school according to the cut-off date regulation and his/her month of birth is used as an instrument for actual school starting age. However, unlike the existing studies, this study uses the control function approach to estimate the effect of school starting age on early academic achievement, as outlined by Garen (1984) and Heckman and Robb (1985). The advantage of the control function approach over the IV approach is that it controls for (a) the bias due correlation of level of unobserved ability and actual school starting age as well as (b) for the individual heterogeneity of the age effect. As discussed above, the standard IV approach only controls for the former bias. Moreover, whereas the IV approach estimates the LATE: the age effect for the "compliers" (those individuals whose school entry age is changed by the instrument), the control function approach estimates the average treatment effect (ATE): the average effect of age on test score for a random individual.

Turning to the results, not surprisingly, the OLS coefficient estimates suggest a negative relationship between school starting age and academic performance, for all three subjects and for all the subsamples under analysis, split by gender and parental education. This negative association is supportive of the notion that, on average, those children who delay school entry come from the lower ability children. The control function approach, which estimates ATE, reverses the relationship between the school starting age and academic performance, that is, the estimate is positive for the full sample for all datasets. The point estimate for the age effect corresponds to 10, 21 and 24 percent of the standard deviation in Reading, Mathematics and Science test scores respectively. The control function approach estimates exceed the corresponding OLS estimates for all of the subsamples considered. Therefore, the paper finds evidence suggesting that starting school at a later age is beneficial for early academic performance.

It is important to note that the OLS estimates are in line with of the international evidence. Among others, Frederikkson and Öckert (2005) for Sweden, Puhani and Weber (2006) for Germany and Bedard and Dhuey (2005) for a number of OECD countries (for example, for Austria, for the Czech Republic and for Portugal) find evidence from OLS regressions for a negative association between academic achievement and actual school starting age, attributing this to the non-random selection of early/late school starters who differ in unobserved academic ability.

Furthermore, the majority of the international evidence finds evidence for a positive age effect using the IV strategy outlined above, with differences in the magnitude across countries and as well as age groups under analysis. One point must be reemphasized, namely that the IV approach yields the LATE estimate, which is equivalent of the age effect for the group of "compliers" (which may not be representative for the population) and is not directly comparable to the estimates of these paper, which yield the ATE estimates. Nevertheless, the estimated age effects from the studies which analyse the same age group, namely grade four students, and the same datasets (but differ somewhat in the covariates included) provide a benchmark for comparison. For example, Puhani and Weber (2006) find the estimated age effect (for the group of "compliers") based on the PIRLS data for German grade four students to be around 40 percent of the standard deviations of the Reading test score in the full German sample. The authors further conclude that German males benefit more than females from later school entry at the grade four level as far as Reading performance is concerned. Moreover, the evidence by Bedard and Dhuey (2005) based on the TIMMS data for a number of OECD countries also suggests a positive age effect for fourth graders in both Science and Mathematics (for the group of "compliers"), differing in magnitude across the countries, ranging from roughly 19 percent to 43 percent of the international standard deviations for the Mathematics test scores for Canada and New Zealand respectively and from around 18 percent to 37 percent of the international standard deviations for the Science test score for Canada and New Zealand respectively.

Although the central variable of interest is the effect of school starting age on academic performance, the effect of the other explanatory variables (which remain similar in sign and magnitude across the subjects and subsamples considered), especially gender, parental education and family size also merit comment, given that there is no extensive evidence for Hungary. First, as expected, the (average) gender achievement gap at the fourth grade level is in favour of girls for Reading and in favour of boys in Mathematics and Science. Whereas, on average, boys attain a lower score in Reading than girls, by approximately 23 percent of the standard deviations in the Reading scores for the full PIRLS sample, they attain a higher score in Mathematics and Science by around 10 and 12 percent of the standard deviation in the Mathematics and Science scores respectively. This is in line with the international evidence explicitly focusing on the effect of gender on academic performance. For instance, Strøm (2004) finds evidence for a gender achievement gap in favour of girls in Reading in Norway using the PISA 2000 data covering 15 – 16 year old students (approximately 33 percent of the standard deviation of the international PISA Reading scores), which is robust across specifications.

Moreover, parental education plays a significant role in educational success in Hungary. For instance, the incremental (mean) Reading score for children whose parents (at least one parent) hold a high school degree relative to those whose parents at most finished primary school is around 89 percent of the standard deviation of the Reading scores. In addition to other factors, this may be driven by the fact that children from high-educated families are more likely to be engaged in activities that promote academic success. Although it is difficult to pin down the direct impact of such parental input on test scores, there are numerous variables in the PIRLS dataset that indicate a positive association between parental education and home activities which promote academic success. For instance, whereas approximately 58 percent of the students with parents having at most primary school degree reported that they are often told stories at home, the corresponding figure for students with parents who possess a college or university degree is 83 percent. Among others, Elder and Lubotsky (2006) and Fertig and Kluve (2005) find evidence for the importance of parental education for schooling success. The latter two authors, based on the "Young Adult Longitudinal Survey" covering 18 – 29 year old individuals, find that in both former East and West Germany children from low educated families (whose parents at most completed the *Hauptschule*) are less likely to attain a high school degree (*Abitur*) and the opposite is true for their counterparts from high educated families (whose parents completed more than *Hauptschule*). Finally, as expected, the number of siblings is a significant determinant of test scores, irrespective of the subject and subsample considered. For example, those students who have more than two siblings score around 46 percent of the standard deviation of the Reading tests lower relative to single children. This finding (a) is supportive of the notion that, on average, families with fewer children have greater endowments in their children's human capital and (b) confirms the international evidence. For instance, Strøm (2004) finds evidence that the number of siblings has a negative effect on the Reading test score using the PISA 2000 data.

Although the study provides evidence that there are positive age effects on early educational attainment, it must be noted that this early and potentially transitory gain in academic achievement, given that the school system is efficient in equalising early inequalities by promoting academic competencies accordingly, must be weighted against (a) the additional childcare costs imposed on the parents in case of delayed school entry (b) the extra economic loss in labour market if the mother only returns to work once the child has started school and most importantly (c) the economic loss in the labour market given that the schooling degree attained and the retirement age is constant. Therefore, the estimation results should only be interpreted as a benefit at the early stage of a child's schooling career.

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APPENDIX 1

Table 1. Descriptive statistics, PIRLS, 2001

	PIRLS (2001)
Variable	
Average reading score	
Overall	544.97
Boys	537.79
Girls	551.80
Academic parents (%)	579.30
Non-academic parents	529.03
Parental education (%)	
Primary school or less	7.95
Vocational degree	42.59
High school degree	12.83
College or university degree	28.11
Missing	8.53
Number of siblings (%)	
Zero	14.84
One	50.74
Two	20.66
More than two	8.85
Missing	4.90
Gender (%)	
Male	48.71
Female	51.29
Car (%)	
Yes	67.73
No	32.27
Mean observed school starting age	6.97
Mean expected school starting age	6.80
Number of observations	4,508

Note: School starting age is measured in years.

Table 2. Descriptive statistics, TIMSS, 2003

	TIMSS (2003)
Variable	
Average mathematics score	
Overall	530.42
Boys	532.45
Girls	528.37
Average science score	
Overall	531.49
Boys	535.04
Girls	527.90
Number of people at home (%)	
Two or three	18.81
Four	42.23
Five	21.66
More than five	14.27
Missing	3.02
Gender (%)	
Male	50.23
Female	49.77
VCR (%)	
Yes	71.03
No	28.97
Usually do well in Mathematics (%)	
Agree a lot	43.76
Agree a little	43.85
Disagree	10.22
Missing	2.17
Usually do well in Science (%)	
Agree a lot	51.52
Agree a little	37.04
Disagree	10.25
Missing	1.18
Mean observed school starting age	7.02
Mean expected school starting age	6.80
Number of observations	3,222

Note: School starting age is measured in years.

Figure 1. Actual school starting age vs expected school starting age (PIRLS 2001)

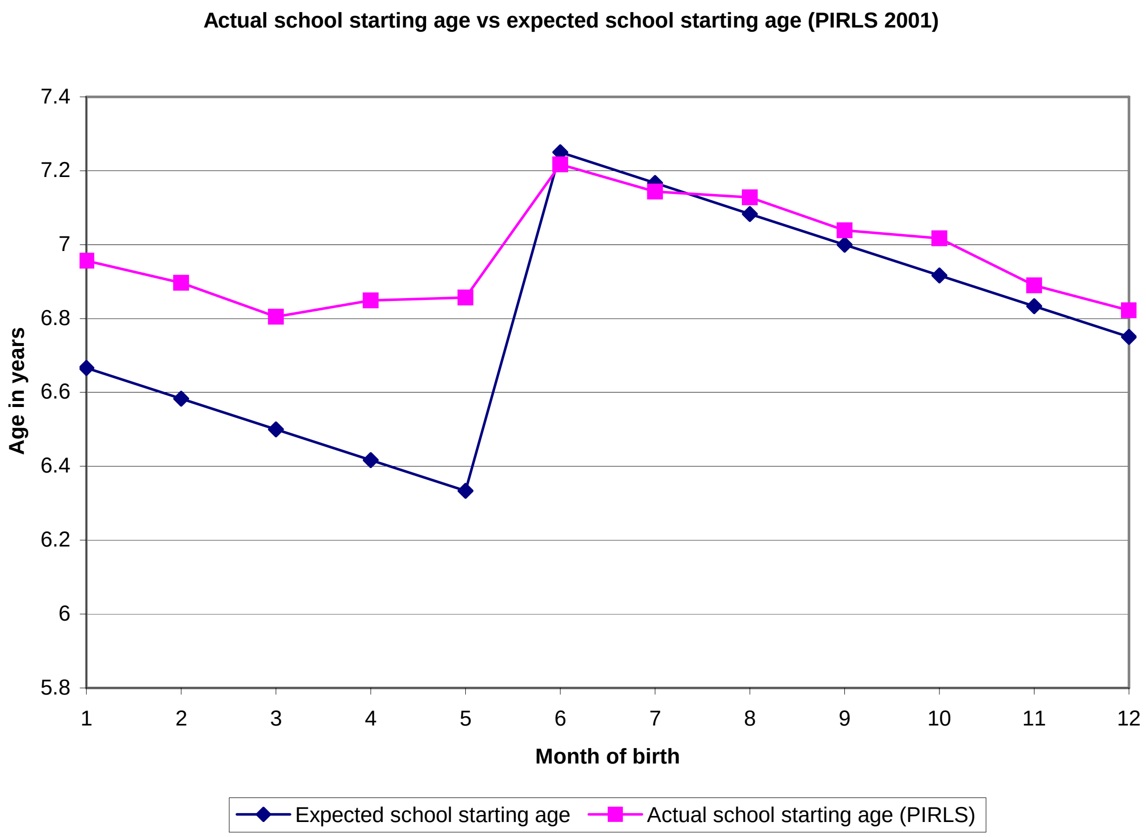
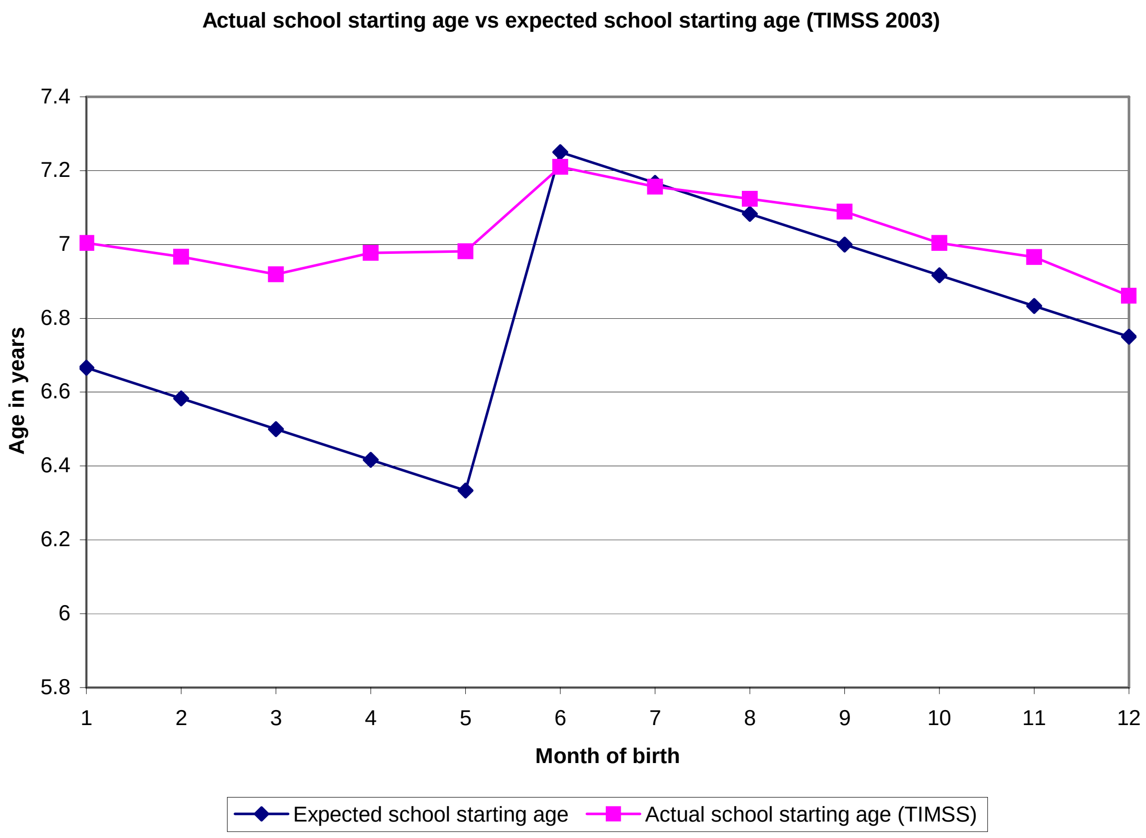


Figure 2. Actual school starting age vs expected school starting age (TIMSS 2003)



APPENDIX 2

Table 3. OLS regression results, PIRLS, 2001

OLS estimates, PIRLS (2001)					
	Entire sample	Boys	Girls	Academic	Non-Academic
School starting age	-16.35	-19.30	-13.64	-5.75	-22.12
	(2.61)	(3.13)	(3.91)	(6.26)	(2.94)
Male	-13.69			-10.57	-15.10
	(1.85)			(3.88)	(2.09)
Car	-15.22	-9.95	-20.10	-12.31	-19.27
	(2.16)	(3.07)	(2.88)	(4.78)	(2.59)
Number of siblings					
One	-3.18	-5.27	-0.77	1.28	-5.80
	(2.33)	(3.49)	(3.66)	(4.70)	(3.17)
Two	-10.19	-13.65	-6.35	2.20	-17.76
	(3.18)	(4.21)	(4.31)	(5.21)	(4.23)
More than two	-27.85	-30.33	-24.84	-13.60	-36.36
	(4.98)	(7.44)	(5.49)	(8.60)	(5.67)
Missing	-25.58	-28.81	-21.21	-16.04	-32.92
	(4.45)	(6.48)	(6.37)	(8.37)	(5.99)
Parental education					
Vocational degree	30.56	30.70	30.96		
	(3.85)	(6.49)	(4.28)		
High school degree	54.10	54.94	53.85		
	(4.68)	(7.36)	(5.21)		
Tertiary degree	76.17	80.70	72.30		
	(4.56)	(6.40)	(5.65)		
Missing	18.07	23.32	13.10		
	(4.90)	(6.50)	(6.18)		
Constant	650.32	650.56	636.82	642.12	732.32
	(19.25)	(23.34)	(28.49)	(40.69)	(20.65)
Observations	4,508	2,232	2,276	1,142	3,003

Notes: 1) School starting age is measured in years. 2) The reference group among the parental education categories is “Primary school or less”. 3) The reference group for number of siblings is “Zero”. 4) Standard errors are in parentheses. 5) Standard errors are adjusted for clustering at school level and are heteroscedasticity robust.

Table 4. First stage and second stage regression results, PIRLS, 2001

Control function approach, PIRLS (2001)		
	First-stage estimates	**Second-stage estimates**
	α_2	γ_2
Entire sample	0.42	6.25
(N = 4,508)	(0.03)	(7.79)
Boys	0.36	13.29
(N = 2,232)	(0.04)	(13.35)
Girls	0.47	1.62
(N = 2,276)	(0.04)	(9.12)
Academic	0.43	10.31
(N = 1,142)	(0.03)	(15.15)
Non-academic	0.44	4.15
(N = 3,003)	(0.05)	(9.38)

Notes: 1) School starting age is measured in years. 2) Control variables included in the regressions are reported in Table 1 in Appendix 1. 3) Standard errors are in parentheses. 4) Standard errors are adjusted for clustering at school level and are heteroscedasticity robust. 5) Standard errors are computed by 1000 bootstrap replications for the second-stage regressions.

APPENDIX 3

Table 5. OLS regression results, TIMSS, Mathematics, 2003

OLS estimates, TIMSS, Mathematics (2003)			
	Entire sample	**Boys**	**Girls**
School starting age	-21.42	-20.82	-21.37
	(3.78)	(3.76)	(5.84)
Male	7.16		
	(2.83)		
VCR	-22.78	-17.91	-27.66
	(3.66)	(3.92)	(5.32)
Number of people at home			
Four	-2.95	2.93	-9.48
	(4.34)	(6.08)	(4.65)
Five	-12.35	-5.97	-19.54
	(4.34)	(6.00)	(5.18)
More than five	-30.87	-16.67	-45.69
	(6.07)	(7.40)	(7.87)
Missing	-78.29	-80.20	-72.08
	(9.04)	(11.91)	(10.03)
Usually do well in Science			
Agree a little	-18.52	-16.88	-20.52
	(2.46)	(3.62)	(3.42)
Disagree	-44.47	-40.01	-49.50
	(4.34)	(6.50)	(5.72)
Missing	-64.82	-66.79	-61.73
	(7.95)	(10.01)	(12.86)
Constant	729.46	719.41	743.04
	(25.47)	(26.99)	(40.54)
Observations	3,222	1,609	1,613

Notes: 1) School starting age is measured in years. 2) The reference group for number of people at home is “Two or three”. 3.) The reference group for „Usually do well in Science“ is „Agree a lot“. 4) Standard errors are in parentheses. 5) Standard errors are adjusted for clustering at school level and are heteroscedasticity robust.

Table 6. First stage and second stage regression results, TIMSS, Mathematics, 2003

Control function approach, TIMSS, Mathematics (2001)

	First-stage estimates	**Second-stage estimates**
	α_2	γ_2
Entire sample	0.27	15.42
(N = 3,222)	(0.03)	(16.49)
Boys	0.16	7.79
(N = 1,609)	(0.05)	(39.50)
Girls	0.37	-9.47
(N = 1,613)	(0.04)	(15.18)

Notes: 1) Variables included in the regressions are reported in Table 2 in Appendix 1. 2) Standard errors are in parentheses. 3) Standard errors are adjusted for clustering at school level and are heteroscedasticity robust. 4) Standard errors are computed by 1000 bootstrap replications for the second-stage regressions.

APPENDIX 4

Table 7. OLS regression results, TIMSS, Science, 2003

	OLS estimates, TIMSS, Science (2003)		
	Entire sample	**Boys**	**Girls**
School starting age	-18.36	-14.98	-21.62
	(3.95)	(3.81)	(5.89)
Male	8.70		
	(2.66)		
VCR	-21.87	-18.94	-24.40
	(3.23)	(3.90)	(4.53)
Number of people at home			
Four	-7.67	-2.94	-12.78
	(3.60)	(4.78)	(4.60)
Five	-12.76	-13.63	-13.28
	(4.20)	(5.57)	(5.32)
More than five	-29.40	-18.64	-39.95
	(5.04)	(6.13)	(6.85)
Missing	-84.69	-86.48	-79.32
	(9.02)	(10.30)	(14.30)
Usually do well in Mathematics			
Agree a little	-33.02	-33.20	-33.13
	(2.58)	(3.82)	(3.73)
Disagree	-54.74	-57.47	-52.66
	(4.67)	(6.95)	(6.32)
Missing	-47.15	-49.11	-47.03
	(11.13)	(12.42)	(17.80)
Constant	718.08	696.21	747.59
	(27.43)	(27.39)	(40.54)
Observations	3,222	1,609	1,613

Notes: 1) School starting age is measured in years. 2) The reference group for number of people at home is “Two or three”. 3.) The reference group for „Usually do well in Mathematics“ is „Agree a lot“. 4) Standard errors are in parentheses. 5) Standard errors are adjusted for clustering at school level and are heteroscedasticity robust.

Table 8. First stage and second stage regression results, TIMMS, Science, 2003

Control function approach, TIMSS, Science (2001)		
	First-stage estimates	**Second-stage estimates**
	α_2	γ_2
Entire sample	0.27	18.18
(N = 3,222)	(0.03)	(16.16)
Boys	0.16	19.56
(N = 1,609)	(0.05)	(38.43)
Girls	0.38	17.56
(N = 1,613)	(0.04)	(16.44)

Notes: 1) Variables included in the regressions are reported in Table 2 in Appendix 1. 2) Standard errors are in parentheses. 4) Standard errors are adjusted for clustering at school level and are heteroscedasticity robust. 5) Standard errors are computed by 1000 bootstrap replications for the second-stage regressions.

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